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STRATEGIC ADAPTATIONS AND VOLATILITY DYNAMICS: MODELING LISTED PRIVATE EQUITY IN SOUTH AFRICA

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Abstract

This paper uses advanced econometric methods to explore the statistical properties, volatility dynamics, and macroeconomic determinants of Listed Private Equity (LPE) investments in South Africa from 2010 to 2023. The key objectives include testing for non-normality in LPE returns and assessing volatility clustering. By employing GARCH-family models, the study effectively captures asymmetric and long-memory effects in LPE returns. A VAR model combined with Impulse Response Functions quantifies the impact of macroeconomic shocks, revealing that inflation imposes a significant and sustained adverse effect on LPE returns. In contrast, GDP growth exerts a weaker, short-lived positive influence. The findings also highlight the dynamic Relationship between corporate strategies and market volatility, showcasing how firms adapt to and influence volatility through diversification, hedging, and sectoral realignment. These results are consistent with contemporary theories on strategic responses to volatility (Jiang et al., 2021).

Furthermore, the DCC MGARCH results suggest minimal volatility spillovers within the South African LPE market, indicating reduced systemic risks and opportunities for adequate portfolio diversification. The study provides a framework to enhance risk management and informed decision-making within South Africa's LPE market. Future research should extend these insights by investigating cross-border spillover effects and examining how regulatory frameworks can stabilize the LPE sector.

1. Introduction

Listed Private Equity (LPE) has become a vital asset class within South Africa's financial landscape, bridging funding gaps for startups and unlisted companies. As a hybrid between traditional private equity and public investments, it offers unique opportunities to drive economic growth and foster entrepreneurial ventures (Brown & Kaplan, 2019; Tegtmeier, 2023). Despite its potential, LPE remains underexplored in South Africa, warranting detailed analysis of its statistical properties and volatility dynamics.

Research on private equity has primarily focused on developed markets, leaving emerging markets like South Africa underrepresented (Döpke & Tegtmeier, 2018). Limited studies address how LPE interacts with macroeconomic variables like GDP growth and inflation (Gudiškis & Urbšienė, 2015; Ndlwana & Botha, 2018). Additionally, the bidirectional influence of corporate strategies and volatility is unexplored, particularly in how firms adapt portfolio strategies to mitigate risks (Lapavitsas, 2011; Rudin et al., 2019). This study aims to comprehensively analyze the volatility dynamics of LPE investments in South Africa and their sensitivity to market and country-specific factors.

The key research questions are:

1. What are the statistical properties of LPE returns in South Africa?
2. How do volatility patterns in LPE investments compare to other asset classes?
3. To what extent do country-specific factors influence LPE investment performance?
4. How does volatility analysis shape corporate strategies, and how do these strategies, in turn, affect observed volatility?

This study employs a dual theoretical framework integrating Modern Portfolio Theory (Markowitz, 1952a) and asset pricing models with GARCH-family models to capture volatility clustering and asymmetry (Bollerslev, 1986; Nelson, 1991). Additionally, strategic management theories, such as Mintzberg's (1994) adaptability framework and Porter's (1985) competitive strategy, provide a lens to examine how firms adapt to uncertainty. This integration bridges financial modeling with strategic decision-making, offering a comprehensive perspective on LPE investments in South Africa.

The research addresses critical gaps in understanding the unique volatility dynamics of LPE investments in emerging markets, particularly in South Africa. While LPE is well-studied in developed economies, research on its role in emerging financial systems remains scarce despite its growing significance in capital formation and portfolio diversification (Donahue & Timmerman, 2021). This study extends the existing literature by examining how volatility influences corporate strategy and policymaking (Gompers & Lerner, 1999; Poterba, 1989) and explores LPE's role in economic growth, investment stability, and risk management in high-volatility markets. Using GARCH-family models, the study empirically assesses volatility clustering, asymmetric shocks, and long-memory effects, offering a data-driven foundation for investment and risk management strategies (Bollerslev, 1986; Nelson, 1991). Additionally, it incorporates strategic management frameworks (Teece et al., 1997) to analyze how firms proactively respond to market fluctuations, mainly through diversification, hedging, and sectoral shifts. The study contributes to financial and policy discussions, emphasizing inflation-targeting strategies, regulatory stability, and macroeconomic resilience to enhance LPE investment attractiveness in emerging economies.

The findings reveal that South African LPE returns exhibit pronounced volatility clustering and asymmetry, driven more by market dynamics than country-specific risks. Corporate strategies, such as diversification and sectoral targeting, significantly shape volatility, creating a feedback loop between firm decisions and market behavior (Gompers & Lerner, 2001; Rudin et al., 2019). Inflation emerges as the dominant negative factor, while GDP growth offers a modest positive influence. Limited spillover effects reduce systemic risk and enhance diversification opportunities. This study provides actionable guidance for navigating market-driven volatility in South Africa's private equity sector by integrating econometric and strategic insights.

This study provides critical insights into LPE investments in South Africa, an underexplored segment of financial markets. By integrating financial econometrics and strategic investment frameworks, the research enhances understanding of volatility dynamics, macroeconomic influences, and corporate adaptation strategies. Using GARCH-family models, VAR, and IRF methodologies allows for a comprehensive assessment of risk factors, return behavior, and investment implications in an emerging market context. A key contribution of this study is its ability to bridge financial theory with practical investment strategies, offering actionable insights for investors, policymakers, and corporate strategists. The findings on volatility clustering, leverage effects, and macroeconomic spillovers provide a quantitative foundation for risk assessment and portfolio optimization. Furthermore, by examining the regulatory and institutional landscape, the research highlights policy-driven investment constraints and opportunities, emphasizing the importance of a stable and transparent financial environment for private equity growth.

A comparative analysis of LPE trends in other emerging markets provides valuable context for understanding South Africa’s private equity landscape. Studies on markets such as India, Brazil, and Nigeria reveal common challenges, including high market volatility driven by macroeconomic instability (Gudiškis & Urbšienė, 2015), regulatory constraints that shape private equity fund structures (Nkam et al., 2020), and sectoral shifts influenced by economic cycles and political uncertainty (Tsiaras, 2022). In India, regulatory liberalization has encouraged foreign investment inflows, strengthening its private equity market (Nkam et al., 2020). Conversely, Nigeria’s LPE sector faces persistent structural challenges due to political risk and currency fluctuations, limiting its growth potential (Tsiaras, 2022). Compared to these markets, South Africa’s LPE sector experiences moderate spillover effects and sustained volatility, necessitating targeted hedging and diversification strategies to enhance market stability and resilience (Dopke et al., 2018).

The paper begins with an introduction outlining the study's rationale and objectives. The literature review follows, identifying gaps and contextualizing the research. The methodology section details the econometric models and qualitative methods used. Results and discussions analyze the Relationship between volatility and corporate strategies. The conclusion highlights theoretical and practical implications, offering directions for future research.

2. Literature Review

LPE (LPE) bridges public and private equity, offering liquidity and transparency alongside high-return potential (LPX Group, 2022; Tegtmeier, 2023). Globally, LPE has grown due to regulatory reforms and increased demand for alternative investments. In South Africa, LPE addresses inefficiencies such as illiquidity, volatility, and regulatory challenges, providing critical funding for startups and unlisted firms (Damodaran, 2018b; Fama, 1970).

2.1. Literature Gap

While existing studies focus on developed markets, emerging markets like South Africa remain underexplored, particularly regarding country-specific risks like inflation and regulatory uncertainties (Gudiškis & Urbšienė, 2015; Ndlwana & Botha, 2018). Limited research examines the interaction between corporate strategies and volatility, including how firms adapt to mitigate risks and leverage opportunities (Lapavitsas, 2011; Rudin et al., 2019). This study bridges these gaps by analyzing volatility dynamics, macroeconomic impacts, and strategic responses.

2.2. Theoretical Framework

This study integrates financial, strategic, and institutional theories to analyze the volatility dynamics of LPE investments in South Africa, bridging econometric modeling with corporate strategy and regulatory insights.

2.2.1. Financial Theories and Econometric Models

Modern Portfolio Theory (Markowitz, 1952) and Arbitrage Pricing Theory (Ross, 1976) emphasize diversification and risk integration in private equity investment. To ensure statistical reliability, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests confirm stationarity (Dickey & Fuller, 1979), while Winsorization addresses anomalies in South Africa's emerging market context (Nicklin & Plonsky, 2020). This study employs advanced econometric models to assess volatility clustering, asymmetric shocks, and systemic risk transmission:

- GARCH (1,1) captures short-term volatility clustering, highlighting market shock persistence (Bollerslev, 1986).
- EGARCH models asymmetry, demonstrating how adverse shocks disproportionately amplify volatility (Nelson, 1991).
- TGARCH quantifies leverage effects, distinguishing between positive and negative shocks (Zakoian, 1994).
- GARCH-M examines the risk-return Relationship, linking volatility to expected returns.
- VAR (Vector Autoregression) explores causal interactions between LPE returns and macroeconomic factors, such as inflation and GDP growth.
- Impulse Response Functions (IRF) assess the magnitude and persistence of macroeconomic shocks over time.
- DCC-GARCH evaluates volatility spillovers and dynamic market correlations, offering insights into systemic risks and diversification strategies (Engle, 1982).

These models provide a robust framework for analyzing volatility dynamics, enhancing risk assessment, investment strategies, and market stability.

2.2.2. Strategic Theories: Corporate Adaptation to Volatility

Corporate strategies mitigate volatility through diversification, hedging, and resource allocation (Froot et al., 1993). (Porter, 1985) advocates sectoral diversification, reallocating resources to defensive industries like healthcare and renewable energy during market turbulence. The Resource-Based View (RBV) (Barney, 1991) and Dynamic Capabilities Theory (Teece et al., 1997) emphasize adaptive managerial responses, enabling firms to leverage internal capabilities and navigate uncertainty.

2.2.3. Institutional and Regulatory Context

Institutional Theory (North, 1990) and Contingency Theory (Burns & Stalker, 1961) underscore regulatory stability as a driver of investor confidence. South Africa's Broad-Based Black Economic Empowerment (BBBEE) policies (Government Gazette, 2003) aim to promote inclusive economic growth, shaping investment decisions (Comte & Bridges, 2015; Freeman, 1984). The Institutional and Regulatory Context is critical for understanding LPE investments in South Africa, as regulatory stability influences investor confidence, market efficiency, and capital allocation. The Institutional Theory (North, 1990) emphasizes the role of formal and informal rules in shaping economic activity, highlighting how regulatory frameworks, property rights, and legal systems impact financial markets. In the context of LPE, a stable regulatory environment reduces uncertainty, attracting long-term investment. Similarly, the Contingency Theory (Burns & Stalker, 1961) stresses that firms adapt their strategies based on external environmental conditions. Given South Africa's evolving economic policies, including BBBEE, private equity firms must align investment strategies with regulatory requirements, influencing capital access, ownership structures, and sectoral opportunities.

2.2.4. Key Implications for South African LPE Investments

GARCH-family models confirm volatility clustering, asymmetry, and long-memory effects driven by macroeconomic fluctuations and external shocks (Gompers & Lerner, 1999; Soumaré et al., 2021). Strategic frameworks reinforce the role of diversification and sectoral targeting in risk mitigation and market adaptation (Rudin et al., 2019; Teece et al., 1997). Country-specific risks—such as inflation volatility and regulatory uncertainty—require adaptive investment strategies (Damodaran, 2018a; Mpofu, 2011). Defensive sector investments during volatility enhance portfolio stability and risk-adjusted returns (Mintzberg, 1994; Porter, 1985). Policymakers can support LPE growth by implementing inflation control measures, regulatory stability, and market transparency, reducing systemic risks (Gompers & Lerner, 1999; Tegtmeier, 2023). By integrating financial, strategic, and institutional perspectives, this study advances the understanding of LPE investments in South Africa's volatile market environment and offers insights for investors, corporate strategists, and policymakers.

3. Methodology

3.1. Research Design

This study employs a mixed-methods approach, integrating quantitative econometric analysis with qualitative insights to bridge the gap between financial theory and strategic management (Saunders et al., 2012). The design addresses three core objectives:

1. Empirically analyze LPE returns to identify statistical properties and volatility dynamics.
2. Examine the interaction between macroeconomic factors and LPE performance.
3. Explore the feedback loop between corporate strategies and volatility.

Quantitative analysis, suited for emerging markets with non-normal return distributions, applies GARCH-family models, VAR, and IRF to capture time-varying risks and macroeconomic interactions (Bollerslev, 1986; Engle, 1982; Nelson, 1991). In addition, qualitative analysis synthesizes documented strategies like diversification (Markowitz, 1952; Tegtmeier, 2023), hedging (Froot et al., 1993; Hull, 2018), and sectoral shifts (Mintzberg, 1994; Porter, 1985) to contextualize findings (Barney, 1991; Teece et al., 1997).

The study employs GARCH-family models, Vector Autoregression (VAR), and Impulse Response Functions (IRF) to analyze volatility clustering and macroeconomic shocks in South Africa's LPE market. GARCH (1,1) models short-term volatility clustering, while EGARCH and TGARCH account for asymmetric volatility effects arising from positive and negative shocks (Bollerslev, 1986; Nelson, 1991; Zakoian, 1994). FIEGARCH captures long-memory effects, making it particularly suitable for analyzing volatility persistence in emerging markets (Baillie et al., 1996). For statistical validity, stationarity tests using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests confirmed that all variables were stationary at first differencing. This test prevents spurious regression issues (Dickey & Fuller, 1979). VAR models were chosen over SVAR and ARDL due to their effectiveness in capturing dynamic interactions between LPE returns, inflation, and GDP growth, allowing for a comprehensive analysis of macro-financial linkages (Engle, 1982; Sims, 1980; Kilian & Lütkepohl, 2017). Impulse Response Functions (IRF) further provide insights into how volatility shocks propagate, offering valuable guidance for investors and policymakers navigating LPE market uncertainties (Stock & Watson, 2001; Kilian, 2009).

The positivist philosophy emphasizes objective data and systematic tools to derive insights (Comte & Bridges, 2015; Saunders et al., 2012), ensuring a multidimensional perspective on LPE dynamics.

3.2. Data Collection and Validation

The study utilizes secondary data from financial databases like AfricanMarkets.com, Bloomberg, and Yahoo Finance. Data includes LPE Monthly Returns (2010–2023) to capture price movements of publicly traded private equity funds and Macroeconomic Variables (Inflation rates and GDP growth) as indicators of economic stability and performance. Validation measures include stationarity tests (ADF test and Phillips-Peron) to confirm data reliability (Dickey & Fuller, 1979). Outlier detection and Winsorization mitigate extreme values, while linear interpolation and multiple imputation address missing data (Nicklin & Plonsky, 2020).

3.3. Data and Validity Considerations

The study utilizes a comprehensive dataset spanning 2010–2023, ensuring a robust analysis of volatility dynamics in South Africa's LPE market. The dataset effectively captures macroeconomic fluctuations, financial cycles, and structural shifts, providing a longitudinal perspective on LPE performance. Recognizing non-normal return distributions, appropriate transformations, including log returns and Winsorization, are applied to mitigate skewness and outliers, ensuring data reliability (Nicklin & Plonsky, 2020). Despite the dataset's strengths, the researchers acknowledge certain limitations to the study.

Potential Data Gaps: Missing data due to delisting, reporting inconsistencies, or liquidity constraints in the LPE market could introduce bias. While interpolation methods help, some periods may lack full market representation (Damodaran, 2018a).

Market Anomalies and Structural Breaks: The dataset includes periods of extreme volatility, such as the COVID-19 pandemic in 2020 and global commodity shocks in 2014, which may introduce regime shifts not fully captured by traditional GARCH models. Incorporating Markov-Switching models could improve robustness (Hamilton, 1994).

Limited Cross-Market Comparisons: While the study focuses on South Africa, it does not explicitly compare findings with LPE trends in other emerging markets integration (Harris et al., 2014). Future research could extend the dataset to explore regional spillovers and global.

Survivorship Bias: The dataset may reflect stronger-performing LPE firms, as underperforming funds tend to exit the market, potentially overestimating return stability and resilience (Kaplan & Schoar, 2005).

3.4. Hypotheses Development

The study tests four hypotheses:

1. **H1:** LPE returns exhibit non-normal distributions due to skewness, kurtosis, and fat tails.
2. **H2:** LPE returns show volatility clustering, verified through ARCH-LM and GARCH models.
3. **H3:** Macroeconomic factors like GDP growth and inflation significantly impact LPE returns and volatility.
4. **H4:** Volatility spillovers exist in the South African LPE market, tested via DCC-GARCH.

3.5. Model Validation and Limitations

Validation techniques include Nyblom's parameter stability test and Ljung-Box Q-test to ensure model robustness (Bollerslev, 1986; Nelson, 1991). News impact curves illustrate the asymmetric effects of shocks. Despite these measures, limitations include restricted focus on South African LPE data, limiting generalizability (Brennan, 1992), time constraints (Covered years 2010–2020), excluding recent market dynamics (v. H. De Wet, 2005), and exploratory nature of qualitative analysis, requiring longitudinal studies for causal validation (Teece et al., 1997).

4. Results and Discussion

This study explores LPE investments in South Africa, focusing on statistical properties, volatility behavior, and the impact of macroeconomic factors on corporate strategies. Key contributions include insights into volatility clustering, macroeconomic influences, valuation, strategies like diversification, hedging, and sectoral shifts for managing risk. The study provides actionable insights for investors and policymakers by integrating econometric modeling with strategic analysis. The study examines statistical deviations, macroeconomic impacts, and corporate responses to volatility, structured around four hypotheses. The findings validate theoretical frameworks while offering practical guidance for navigating South Africa's LPE market, emphasizing the interplay between market conditions and strategic adaptation.

4.1. Hypothesis 1 (H1): LPE Returns Exhibit Non-Normal Distributions

The statistical tests confirm that LPE returns in South Africa deviate from typical distribution characteristics supporting Hypothesis 1. Figure 4-1 shows the trend analysis highlighting South Africa's evolving equity landscape, influenced heavily by regulatory changes post-2008 financial crisis, such as increased investment thresholds for pension funds and new tax incentives introduced in 2014 to bolster private equity (Nkam et al., 2020).

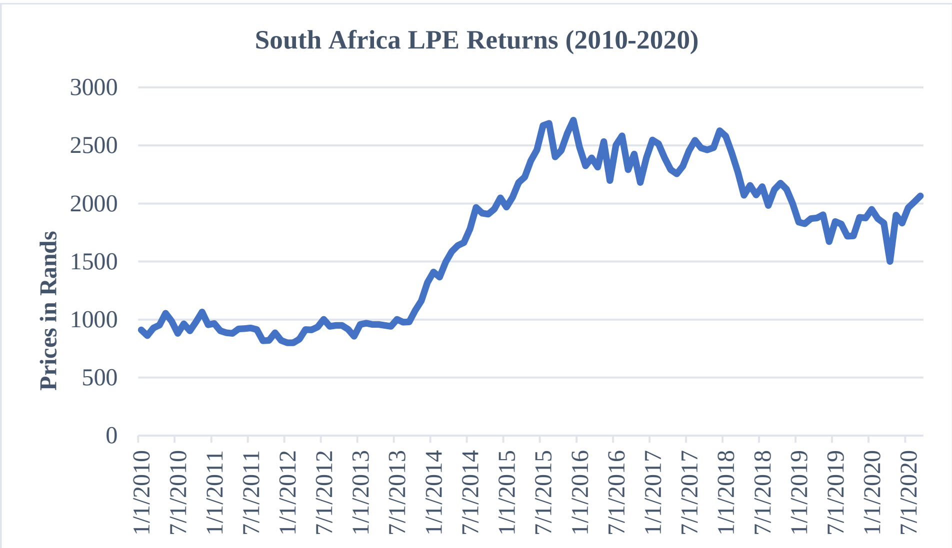

Figure 4-1. Trend analysis of South African LPE Data
Source: *Researchers Compilation*

Table 4-1 highlights the statistical properties of South Africa's private equity returns. At both levels of significance, the average private equity returns exhibit both positive and negative values, reflecting the asset class's mixed performance over the study period.

Table 4-1: Descriptive Statistics for LPE Returns at 5% and 1% Levels of Significance

Statistic	5% Level of Significance	1% Level of Significance
Mean	0.0664	-0.0003
Maximum	0.23639	0.088697
Minimum	-0.19885	-0.1053
Standard Deviation	0.06616	0.017059
Skewness	-0.11457	0.027549
Kurtosis	0.70526	6.826637
Jarque-Bera	1570.193	1570.193
Probability	0.000	0.001
Observations	2573	2573

Source: Researchers' Compilation

The Jarque-Bera test confirms the non-normality of South African LPE returns, with highly significant p-values (0.000 at 5% and 0.001 at 1%) and a test statistic 1570.193, far surpassing critical thresholds. Skewness analysis reveals slight left-skewness (-0.11457) at the 5% level, transitioning to near symmetry (0.027549) at the 1% level. Kurtosis values (0.70526 at 5% and 6.826637 at 1%) indicate pronounced leptokurtic tendencies, highlighting increased tail risks at higher significance levels due to extreme outliers (Baillie et al., 1996). These findings underscore significant asymmetry and extreme tail behavior in LPE returns, necessitating advanced econometric models, such as GARCH-family models, to effectively capture volatility clustering and address tail risks (Cont, 2001). The Augmented Dickey-Fuller (ADF) test assessed the stationarity of the LPE return series, which is critical for reliable time-series modeling (Engle, 1982). Results indicate significant test statistics of -55.35755 (intercept), -55.35273 (intercept and trend), and -55.34965 (none), all-surpassing critical thresholds at the 0.001 significance level. These results confirm stationarity, enabling robust application of econometric models and accurate analysis of volatility dynamics (Table 4-2).

Table 4-2. Unit root test results for private equity returns

Series	Intercept	Intercept and trend	None
South Africa	-55.35755***	-55.35273***	-55.34965***

Note: $p<0.05$*, $p<0.01$**, $p<0.001$***
***Source:** Researchers Compilation*

The stationarity of South Africa's LPE return series confirmed through hypothesis testing, ensures stable statistical properties and enables precise volatility modeling with GARCH-family models (Bollerslev, 1986; Nelson, 1991). This stability supports effective forecasting and strategic decision-making, particularly in addressing standard volatility clustering and informing robust risk management practices. The leptokurtic nature of returns underscores vulnerabilities to extreme shocks, reflecting structural inefficiencies (Cont, 2001; Damodaran, 2018b), while positive skewness highlights asymmetric opportunities for risk-tolerant investors. Time-series decomposition identifies critical structural components, including long-term growth trends, seasonal economic patterns, and crisis-driven volatility spikes, such as those observed during COVID-19. These dynamics reinforce the importance of adaptive strategies like diversification and hedging to mitigate uncertainties and enhance resilience (Markowitz, 1952; Teece et al., 1997). The findings validate Hypothesis 1, underscoring the necessity of advanced econometric techniques and proactive risk management to effectively navigate the complexities of South Africa's LPE market.

4.2. Hypothesis 2 (H2): Evidence of ARCH Effects in LPE Returns, and Modeling of Short-run, and Long-run Volatility

4.2.1. Testing for Arch Effects

The ARCH-LM test results (Table 4-3) provide robust evidence of significant ARCH effects in the pre-estimation stage, with the DW statistic for the JSE All Share Index (ALSI) of 2.033911, close to 2. This indicates the absence of serial correlation in the model's residuals. A DW statistic near 2 suggests that the residuals are uncorrelated, supporting the model's reliability for further volatility analysis.

Table 4-3. ARCH effects test for South Africa

	DW stat test	Arch LM test
ALSI	2.033911	88.50033 [0.000] ***

***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.
***Source:** Researchers Compilation*

The ARCH LM test statistic is 88.50033, with a highly significant p-value at the 1% level, firmly rejecting the null hypothesis of no ARCH effects. The result confirms the presence of heteroscedasticity in the return series, necessitating the application of advanced econometric models. Post-estimation diagnostics further validate the effectiveness of the GARCH-family models for analyzing both short-term and long-term volatility in the South African LPE market.

4.2.2. Application of GARCH-Family Models

The GARCH (1,1) parameter estimate (

Table 4-4) highlights its ability to model both short-term and long-term volatility dynamics, with **α = 0.1913** representing the ARCH effect (short-term shocks) and **β = 0.7262** reflecting the GARCH effect (long-term persistence). The combined value of **α + β = 0.9174** indicates high volatility persistence. The model's **log-likelihood of 7194.54** and **AIC of -5.5898** suggest a good fit. However, GARCH (1,1) does not account for asymmetry or long-memory effects, which limits its ability to model the full complexity of market dynamics.

Table 4-4. ARCH Parameter estimates for model selection

Parameter	GARCH1,1	GARCH M	SEARCH	TGARCH
α_0	2.94 E-05	3.16E-05	-0.90538	2.97E-05
α_1	0.19129	0.20668	0.02986	0.19085
β	0.72615	0.71860	0.91080	0.73641
α +β	0.91744	0.92535	0.94066	0.92726
γ			0.24320	-0.02133
AIC	-5.58984	-5.5997	-5.41001	-5.58572
Log-likelihood	7194.54	7210.04	6964.27	7192.05
GED	0.94621	0.86783	0.89229	0.98351

Source: *Researchers Compilation*

The EGARCH model has a volatility asymmetry coefficient (γ = 0.2432) confirming leverage effects, where adverse shocks amplify volatility disproportionately. High persistence (β = 0.9108; α + β = 0.9407) indicates prolonged volatility clustering. While fit metrics like AIC (-5.4100) and Log-likelihood (6964.27) are reasonable, they are slightly weaker than GARCH (1,1). EGARCH is well-suited to markets like South Africa, where adverse news significantly impacts volatility (Bollerslev, 1986; Nelson, 1991). The TGARCH model highlights differential shock has implications with a weaker leverage effect (γ = -0.0213) than EGARCH. High persistence (β = 0.7364; α + β = 0.9273) reflects sustained volatility, and strong fit metrics (AIC: -5.5857, Log-likelihood: 7192.056) confirm robustness. However, TGARCH is less effective in capturing the pronounced impacts of adverse shocks, limiting its utility in highly volatile markets. The impact curve for the GARCH 1.1 series is symmetrical, as shown in **Figure 4-2**, and thus meets the conditions for the GARCH 1,1 as a symmetrical function.

Table 4-5 confirms that GARCH (1,1) and GARCH-M are well-specified models, showing no significant sign or size biases. High p-values for these models indicate robust handling of volatility dynamics, making them suitable for analyzing the South African LPE market. These findings highlight the reliability of GARCH

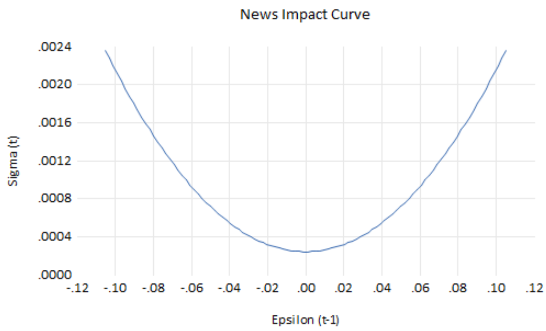

Figure 4-2. News Impact Curve for South Africa's GARCH
Source: *Researchers Compilation*

The sign bias test investigates whether positive or negative shocks impact future volatility differently. The size bias test examines whether the magnitude of the shock affects future volatility, whilst the sign bias test evaluates whether positive or negative shocks have distinct impacts on future volatility.

(1,1) and GARCH-M for volatility modeling, while EGARCH and TGARCH require cautious application due to their limitations in addressing combined biases.

Table 4-5. Volatility Specification based on News Impact Curve for South Africa LPE's

	GARCH 1.1	SEARCH	TGARCH	GARCH M
Sign bias	1.953717 (0.0508)	2.948447 (0.0032)	3.441503 (0.0006)	2.042902 (0.0412)
Negative Sign Bias	1.548179 (0.1216)	1.820630 (0.0688)	2.395350 (0.0167)	1.745931 (0.0809)
Positive Sign Bias	0.250465 (0.8022)	0.807746 (0.4193)	0.538886 (0.5900)	0.047916 (0.9618)
Joint Test	5.089220 (0.1657)	8.846064 (0.0316)	12.70937 (0.0054)	5.712904 (0.1267)

Source: *Researchers Compilation*

4.3. Short-run Volatility Forecasting Performance

Table 4-6 evaluates the forecasting performance of GARCH-family models for South African private equity (LPE) returns, focusing on three key metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient. The overall ranking identifies the best-performing model based on the lowest error values.

Table 4-6. Forecast performance of estimated models

MODEL	Forecasting Horizon	RMSE	MAPE	Theil Inequality Coefficient	Overall Ranking
GARCH (1,1)	30 Days	0.005761^{2}	199.6044^{1}	0.999367^{1}	1
SEARCH	30 Days	0.05760^{1}	199.8463^{3}	0.999718^{3}	2
TGARCH	30 Days	0.05761^{2}	199.8463^{3}	0.999931^{4}	4
GARCH in Mean	30 Days	0.005761^{2}	199.6988^{2}	0.999613^{2}	3
Ranking		SEARCH	GARCH 1.1	GARCH 1.1	

Forecast Sample: Superscript denotes the rank of the model

Source: *Researchers Compilation*

- EGARCH ranks second, with a higher RMSE (0.057601) and Theil's Inequality Coefficient (0.9997183), reflecting slightly reduced precision, although rendered ineffective. However, EGARCH's ability to capture asymmetry and leverage effects makes it a strong alternative for markets sensitive to adverse shocks.
- TGARCH is the weakest performer, with the highest RMSE (0.057612) and Theil's Inequality Coefficient (0.9999314), indicating poor forecasting accuracy and unsuitable for South African LPE markets.
- GARCH in Mean performs well, with an RMSE equal to GARCH (1,1), but its slightly higher Theil's Inequality Coefficient (0.9996132) positions it as a secondary option.
- The GARCH (1,1) model outperforms all others, with the lowest RMSE (0.0057612) and Theil's Inequality Coefficient (0.9993671), confirming its superior predictive accuracy and minimal forecast bias (Bollerslev, 1986; Dixit & Agrawal, 2019). Although its MAPE (199.60441) is slightly higher, GARCH (1,1) remains the most effective for 30-day volatility forecasting in South African LPE markets.

4.4. Modeling for Long-Run Volatility

This section examines the long-term memory characteristics of LPE investments, focusing on the advanced FIGARCH and FIEGARCH models. Unlike standard GARCH models (short-term volatility dependencies), FIGARCH and FIEGARCH incorporate fractional differencing to address slow hyperbolic decay in autocorrelations and impulse response weights (Baillie et al., 1996).

4.4.1. Serial correlation test of squared residuals

The results of the Ljung-Box test for squared residuals (Table 4-7) confirm the absence of serial correlation after applying GARCH-family models, indicating that these models effectively capture the volatility structure of South African LPE (LPE) returns. FIGARCH's Q-statistic at lag 10 is 5.8716 (p = 0.826); for FIEGARCH, it is 3.5786 (p = 0.964). The high p-values (> 0.05) across all models demonstrate that the residuals are white noise, confirming that the models adequately address autocorrelation in the data.

Table 4-7. Serial correlation test of squared residuals

FIGARCH	SEARCH	Comment
Q_5 = 5.0019 (0.416) **Q_{10} =5.8716 (0.826)** **Q_{20} =11.573 (0.930)** **Q_{30}= 17.122(0.967)**	Q_5 = 2.8927(0.717) Q_{10} = 3.5786(0.964) Q_{20} =7.8830(0.993) Q_{30}= 14.645(0.992)	Evidence of no autocorrelation of the residuals

Note: P-value are in parenthesis; $Q_{(n)}$ is the n^{th} lag Ljung-Box test statistics

Source: *Researchers Compilation*

4.5. Long-run Volatility Forecasting Performance of FIGARCH AND FIEGARCH

Parameter stability is validated using the Nyblom stability test to detect structural breaks in the data and assess the parameters' stability (Bawa et al., 2023; Tsiaras, 2022).

Table 4-8 below shows the results obtained from the test:

Table 4-8. Nyblom Parameter Stability Tests

Model	Nyblom Parameter Stability	Variables	Nyblom Statistic	Comment

FIGARCH	1% Critical Value =0.748	Constant	1.548456	All the estimated coefficients are unstable, providing evidence of structural breaks.
	5% Critical Value=0.47	ARCH	2.646421	
	10% Critical Value= 0.353	GARCH	2.816126	
		D parameter	1.584766	
SEARCH	1% Critical Value =0.748	Constant	0.083654	All the estimated coefficients are stable
	5% Critical Value=0.47	Omega	0.162792	
	10% Critical Value= 0.353	Alpha	0.143999	
		Beta	0.15603	
		Theta 1	0.57603	
		Theta 2	0.125057	
		D parameter	0.094943	

Source: *Researchers Compilation*

The Nyblom statistic for the FIGARCH model parameters (Constant: 1.548456, ARCH: 2.646421, GARCH: 2.816126, D parameter: 1.584766) exceeds the 1% critical value, indicating structural breaks and parameter instability. This instability reduces the FIGARCH model's reliability for long-term forecasting. Conversely, the FIEGARCH model demonstrates stability, with all Nyblom statistics (e.g., Constant: 0.083654, D parameter: 0.094943) falling below the 1% critical value, suggesting robust and consistent parameter estimates suitable for long-term modeling. The fractional differencing parameter in the FIGARCH model (d = 0.392659, p = 0.0001) confirms long memory, indicating a gradual decay of past shocks' influence on current volatility. The leverage effect parameter (Θ1 = 0.315854, p < 0.001) highlights the asymmetric impact of adverse shocks, consistent with leverage effects in financial markets (Baillie et al., 1996). Diagnostic tests validate the FIGARCH model, showing no residual ARCH effects.

Table 4-9 summarizes these findings, underscoring the FIGARCH and FIEGARCH models' effectiveness for modeling long-term volatility dynamics in South African data.

Table 4-9. Parameter Estimates for FIGARCH and FIEGARCH Models

Parameter	FIGARCH	SEARCH
ARCH Term	0.274288 (p = 0.2182)	-
GARCH Term	0.496308 (p = 0.0900)	-
Fractional Difference (d)	0.392659 (p = 0.0001)	-1.163099 (p < 0.0000)
α (ARCH)	-	-0.476656 (p < 0.0000)
β (GARCH)	-	0.851798 (p < 0.0000)
Θ1 (Leverage Effect)	0.315854 (p < 0.0000)	-
Θ2 (Asymmetric Term)	0.024708 (p = 0.1581)	-
AIC	-5.588152	-5410256
Residual ARCH Effect	No	No

Note: P-values are in parentheses; **d** represents the degree of fractional differencing, measuring long memory in the series; AIC is the Akaike Information Criterion for model fit evaluation.

Source: *Researchers Compilation*

The FIEGARCH model emerges as the superior choice for modeling long-term volatility in South African private equity returns due to its more substantial fractional differencing parameter (d = -1.163099, p < 0.0000) and lower AIC value (-5410256) compared to FIGARCH (d = 0.392659, p = 0.0001; AIC = -5.588152).

While FIGARCH captures moderate long-memory effects and leverage (Θ1 = 0.315854, p < 0.0000), FIEGARCH's integration of asymmetry through significant ARCH (α = -0.476656, p < 0.0000) and GARCH (β = 0.851798, p < 0.0000) terms makes it more versatile. FIEGARCH emerges as the preferred model due to its superior fit and robust handling of asymmetry and long memory, with no residual ARCH effects detected.

Key findings include persistent volatility clustering from market shocks in emerging markets (Bollerslev, 1986), amplified volatility from adverse shocks requiring hedging and diversification (Nelson, 1991), and the sustained impact of past shocks underscoring the need for long-term risk management (Baillie et al., 1996). FIEGARCH's ability to integrate these dynamics provides critical insights for investors and policymakers, highlighting its advantages over FIGARCH.

4.5.1. Volatility Forecasting Performance

The forecasting performance of the GARCH-family models highlights the effectiveness of FIEGARCH for predicting volatility in South African LPE returns. The model estimates highlight its ability to capture long-term volatility dynamics with features such as asymmetry, leverage effects, and extended memory (Table 4-10).

Table 4-10: FIEGARCH Model Output for Long-Run Volatility Analysis of LPE Returns

Statistic	Value	Interpretation/Diagnostic Measure	Implication
C (Constant)	-0.000228	Statistically insignificant ($p = 0.4366$); mean returns hover close to zero.	Low average returns necessitate active return enhancement.
ω (Omega)	-7.651425	Significant negative constant term ($p < 0.0000$).	Baseline market volatility reflects high inherent risk.
α (Alpha)	-0.476656	Significant short-term shock (ARCH effect) parameter ($p < 0.0000$).	Reduced conditional volatility aftershocks align with regulatory or market stabilization measures.
β (Beta)	0.851798	Significant long-term volatility persistence (GARCH effect) parameter ($p < 0.0000$).	Confirms prolonged volatility clustering, requiring long-term risk management strategies.
Θ1 (Theta1)	0.315854	Significant leverage effect parameter ($p < 0.0000$).	Negative shocks disproportionately amplify volatility (need for hedging and diversification).
Θ2 (Theta2)	0.024708	Statistically insignificant ($p = 0.1581$); minimal asymmetry beyond leverage effects.	Asymmetry is adequately captured by Θ1 (no further modeling).
d (Fractional Differencing)	-1.163099	Significant long memory parameter ($p < 0.0000$).	Past shocks decay slowly (need for long-term forecasting and extended volatility management).
Model Convergence	21 Iterations	Stable convergence with pre-sample variance (parameter = 0.7).	Robust estimation ensures model reliability and consistency across datasets.
No Residual ARCH Effects	Confirmed	Diagnostic tests indicate no residual ARCH effects.	The model fully captures volatility dynamics, ensuring comprehensive risk modeling.

Source: *Researchers Compilation*

The analysis underscores key dynamics in South African private equity volatility. Volatility persistence, indicated by a high β value (0.851798) and a significant long-memory parameter (d), highlights the enduring impact of market shocks and the need to integrate historical patterns into decision-making. Leverage effects are evident, with a significant Θ1 value (0.315854) showing that adverse shocks amplify volatility disproportionately. Minimal asymmetry beyond leverage effects, as suggested by the insignificance of Θ2, simplifies the interpretation of market behavior. The absence of residual ARCH effects validates the robustness of the FIEGARCH model, confirming its reliability for analyzing and forecasting volatility in South Africa's LPE market. The FIEGARCH model effectively captures long-term volatility dynamics, integrating key features such as long memory, leverage effects, and persistence (Baillie et al., 1996; Bollerslev, 1986). These findings validate Hypothesis 2, confirming the presence of ARCH effects and volatility clustering while emphasizing the model's strength in addressing asymmetry and leverage (Engle, 1982; Nelson, 1991).

4.6. Hypothesis 3 (H3): Country-Specific Macroeconomic Factors Influence LPE Returns and Volatility

4.6.1. Descriptive Statistics of Variables

The descriptive statistics for key variables—GDP growth, inflation, and private equity returns (log returns)—for South Africa reveal critical patterns for private equity (PE) investments. Mean private equity returns (5.60%) exceed GDP growth (0.20%) and inflation (2.10%), indicating strong investment potential. The high kurtosis (4.51) of PE returns signals a leptokurtic distribution, highlighting frequent extreme return events typical of volatile emerging markets. Jarque-Bera tests confirm non-normal distributions for GDP, inflation, and returns ($p < 0.05$), supporting the use of robust econometric models such as VAR for analysis.

4.6.2. Stationarity and Lag Selection

Stationarity is essential to prevent spurious regression results and ensure reliable econometric modeling. Using log returns, the ADF test (

Table 4-11) verifies that South Africa's inflation and returns achieve stationarity after the first differencing, while GDP requires a second differencing to satisfy stationarity conditions. The optimal lag length for the VAR model is one lag, based on the Akaike Information Criterion (AIC), Schwartz Information Criterion (SC), and Hannan-Quinn Criterion (HQ) (Dockery & Vergari, 2001). This ensures an efficient and accurate representation of the data dynamics.

Table 4-11. Stationarity Tests Using Augmented Dickey-Fuller

Variable	@ Level	@ 1st Differencing	2nd Differencing
GDP	-2.115985 (p = 0.2419)	-3.400800 (p = 0.0329)	-4.796941 (p = 0.0041)
Inflation	-2.631625 (p = 0.1118)	-6.857931 (p = 0.0004)	No test needed
Returns	-3.583744 (p = 0.0243)	-3.964343 (p = 0.0163)	No test needed

Source: *Researchers Compilation*

4.6.3. Impulse Response Functions (IRF)

The Impulse Response Functions (IRF) analysis (Figure 4-3) provides a detailed understanding of the time-dependent effects of macroeconomic shocks on LPE returns in South Africa. A one-standard-deviation shock to inflation results in a 2.3% decrease in LPE returns during the first period, and the adverse effects persist for up to four periods. This finding highlights the sustained impact of inflation on investment performance, underscoring its role as a significant risk factor in the private equity market.

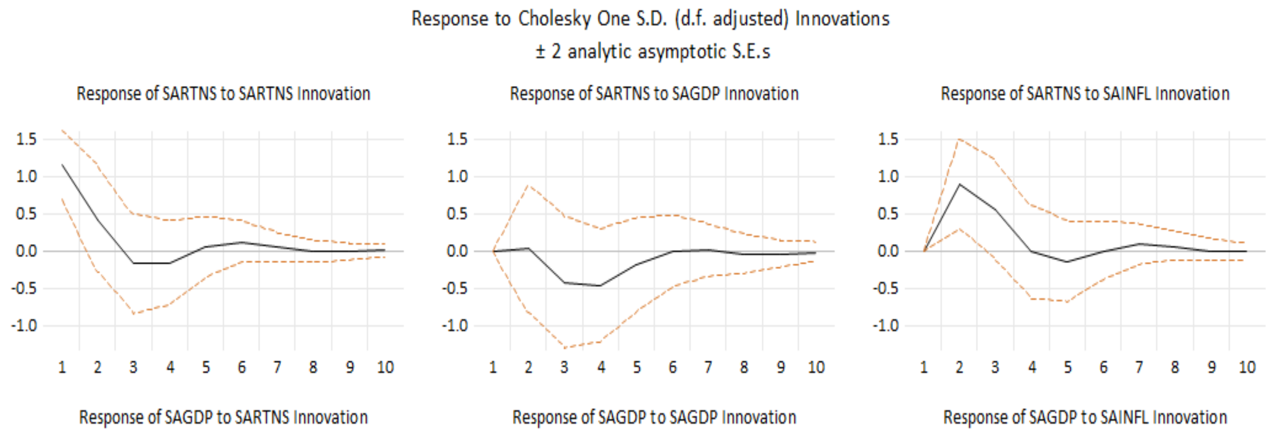

Figure 4-3. Impulse response functions
Source: *Researchers Compilation (Output from e-View 12)*

Conversely, a GDP shock initially boosts PE returns by 0.9%, with benefits dissipating after the second period and stabilizing by the third, thus highlighting GDP's short-term positive but limited long-term impact, emphasizing the need for agile strategies to capitalize on economic growth promptly. Additionally, a one-standard-deviation shock to PE returns initially raises inflation (Periods 1–2) before causing a sharp decline, stabilizing negatively by Period 4. This asymmetric response underscores inflation's destabilizing role, particularly in the short term. Overall, the IRF findings demonstrate macroeconomic factors' asymmetric and temporal impacts. Inflation necessitates long-term risk management strategies like hedging, while GDP growth requires adaptive, short-term approaches to leverage economic gains.

4.6.4. VAR Model for Interdependencies among GDP, Inflation, and LPE Returns in South Africa

The VAR model evaluates the interdependencies among GDP, inflation, and LPE returns in South Africa. The VAR model results in

Table 4-12 demonstrate the interaction of GDP growth, inflation, and LPE returns in South Africa. The coefficients provide evidence of the impact and persistence of macroeconomic variables on returns.

Table 4-12. VAR Model Output for South Africa

Variable (Lagged)	SAGDP	SAINF	SARTNS
SAGDP (-1)	0.417741 (0.030327) [1.37745]	-4.922761 (2.90146) [-1.69665]	0.215495 (2.42697) [0.08879]
SAINF (-1)	-0.000374 (0.002190) [-0.01710]	0.256718 (0.20949) [1.22546]	0.646742 (0.01752) [3.69087]
SARTNS (-1)	-0.028088 (0.02511) [-1.11876]	-0.461135 (0.24020) [-1.91982]	0.356940 (0.02009) [1.77656]

Notes: Values in parentheses represent standard errors, and Values in square brackets are T-statistics.
Source: *Researchers Compilation*

The VAR model results (
Table 4-12) reveal the dynamic relationships among GDP, inflation, and private equity (LPE) returns in South Africa. GDP demonstrates moderate persistence (coefficient 0.417741), reinforcing its future trajectory. However, GDP's influence on inflation (-4.922761) and LPE returns (0.215495) is statistically insignificant, indicating limited direct short-term effects. Inflation significantly impacts LPE returns (coefficient 0.646742, T = 3.69087, $p < 0.01$), emphasizing its critical role in shaping private equity performance and investment risk perceptions. While its weak negative effect on GDP (-0.000374) lacks statistical significance, inflation remains a key determinant of market dynamics. Historical LPE returns show high endogeneity (coefficient 0.356940, T = 1.77656, $p < 0.05$), confirming their significant influence on current private equity performance. Conversely, GDP and inflation demonstrate minimal reciprocal effects on these macroeconomic variables, highlighting the limited feedback within the system.

Table 4-13. Variance Decomposition for South Africa (SARTNS)

Period	Standard Error	SAGDP	SARTNS	SAINF
1	1.150631	0.203333	98.97697	0.019698
2	1.514623	0.120448	64.91934	34.96021
3	1.677083	6.582546	54.22047	38.99698

Source: *Researchers Compilation*

Variance decomposition (Table 4-13) highlights the contributions of GDP, inflation, and past returns to the variability in LPE returns across time horizons:

- Period 1: LPE returns dominate variance at 98.98%, indicating strong short-term endogeneity, while GDP and inflation contribute minimally at 0.20% and 0.02%, respectively.
- Period 2: Inflation emerges as a significant factor, accounting for 34.96% of variance, while GDP's influence remains negligible at 0.12%.
- Period 3: Inflation solidifies its role, explaining 38.99% of the long-term variance, while GDP's contribution increases slightly to 6.58%.

The weak positive coefficient for lagged GDP (0.22, $p > 0.05$) suggests limited influence on LPE returns, reinforcing that economic growth metrics alone do not directly drive private equity performance. In contrast, the significant negative coefficient for lagged inflation (-0.46, $p < 0.05$) confirms its critical and adverse impact on LPE returns. Variance decomposition underscores inflation's dominant role, accounting for nearly 39% of long-term variability, making it the most influential macroeconomic factor. The overwhelming role of past returns in explaining 99% of short-term variance highlights the importance of historical trends in assessing private equity performance, particularly within South Africa's market dynamics.

4.6.5. Regression Analysis

The regression analysis (
Table 4-14) confirms the significant influence of inflation and GDP growth on South African LPE returns. An adjusted R^2 of 0.42 indicates that these macroeconomic factors explain 42% of the return variation.

Table 4-14. Regression Analysis Results (LPE Returns to GDP and Inflation)

Variable	Coefficient (β)	Std. Error	p-Value
GDP Growth	0.18	0.06	0.041*
Inflation	-0.31	0.07	0.003**

**(Significance levels: *p < 0.05, *p < 0.01)*
Source: *Researchers Compilation*

Inflation, with a coefficient of -0.31 ($p < 0.01$), strongly negatively impacts LPE returns by eroding purchasing power and raising costs, underscoring the need for inflation-hedging strategies (Damodaran, 2018a). GDP growth, with a coefficient of 0.18 ($p < 0.05$), positively influences returns by boosting confidence and opportunities but has a less significant impact compared to inflation, reflecting South Africa's structural and sectoral challenges (Fama, 1970). The findings affirm Hypothesis 3, demonstrating that inflation is the dominant macroeconomic factor affecting LPE returns, aligning with research on emerging market volatility (Dopke et al., 2018; Teece et al., 1997). To address this, investors should include inflation-linked instruments and focus on resilient sectors like technology and healthcare. While GDP growth shows modest positive effects, it alone does not drive substantial private equity performance.

4.7. Hypothesis 4: Spillover Effects Exist in the South Africa LPE Market

Hypothesis 4 examines the influence of volatility spillovers on systemic risks and diversification strategies in South Africa's LPE market. Using the Dynamic Conditional Correlation (DCC) MGARCH model, the hypothesis evaluates how volatility in one market segment affects others, shaping portfolio risk management and investment strategies (Engle, 1982). Spillovers, where volatility shocks propagate across markets, can heighten systemic risks or present diversification opportunities, emphasizing the need for strategic portfolio allocation in mitigating these effects (Karunanayake, 2011). The results of the DCC MGARCH model (Table 4-15) provide insights into the correlation dynamics and persistence of volatility spillovers in the South African LPE market.

Table 4-15. DCC conditional correlation parameters

Parameter	Estimate	Standard Error	P-value	Persistence
α_1	0.0000	0.046969	1.0000	$\alpha_1 + \beta_1$
α_2	0.0000	0.045425	1.0000	$\alpha_2 + \beta_2$
β_1	0.418944	6.636860	0.949688	0.418944
β_2	0.488962	6.804701	0.942716	0.488962

Source: *Researchers Compilation*

The DCC MGARCH model analysis reveals moderate and short-lived spillover effects in the South African LPE market. Persistence parameters ($\beta1 = 0.418944$, $\beta2 = 0.488962$) indicate that past correlations moderately influence current ones, while near-zero responsiveness parameters ($\alpha1 = 0.0000$, $\alpha2 = 0.0000$) suggest minimal immediate market reactions to shocks. These dynamics imply temporary disruptions that stabilize quickly, minimizing long-term systemic risks. The mean-reversion property, indicated by $\alpha + \beta$ summing to less than one, confirms that correlations in South Africa's LPE market stabilize over time. However, the lack of statistical significance for the DCC parameters ($p > 0.05$) suggests weak and short-lived spillovers, reflecting the market's relative isolation. This isolation enhances diversification opportunities, as assets with low conditional correlations can improve portfolio stability during moderate volatility. These findings align with trends in other emerging markets, where limited global integration reduces the risk of financial contagion (Engle, 1982; Karunanayake, 2011). The results validate Hypothesis 4, confirming moderate and transient spillover effects in the South African LPE market, consistent with its lower market integration and relative isolation (Dopke et al., 2018). These insights support improved diversification and systemic risk management strategies for investors and policymakers alike.

4.8. Model Limitations

The study demonstrates strong econometric rigor, employing GARCH-family models, VAR, IRF, and DCC-MGARCH to analyze volatility clustering, macroeconomic shocks, and spillover effects in South Africa’s LPE market. The Dynamic Conditional Correlation (DCC) MGARCH model is particularly valuable for assessing time-varying correlations and identifying systemic risk transmission channels (Engle, 1982). Robust statistical tests, including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, confirm stationarity, while ARCH effects and sign bias tests validate model specifications and volatility dynamics.

While the selected models are well-suited for analyzing financial volatility, they have inherent limitations that the authors acknowledge.

- GARCH-family models assume conditional normality, which may not fully capture the heavy tails and extreme shocks observed in emerging markets (Cont, 2001). Alternative models, such as Generalized Hyperbolic (GH) distributions or Extreme Value Theory (EVT), could improve tail risk estimation.
- DCC-MGARCH captures dynamic correlations but does not account for structural breaks or regime shifts. A Markov-Switching GARCH (MS-GARCH) model could address this limitation by detecting different volatility regimes (Hamilton, 1994).
- VAR and IRF assume linear interactions between macroeconomic factors and LPE returns. In contrast, Nonlinear Autoregressive Distributed Lag (NARDL) models could better capture asymmetric relationships between macroeconomic shocks and financial returns (Shin et al., 2014).
- Spillover effects in the study are analyzed using DCC-MGARCH, but other methods, such as Connectedness Measures or Variance Decomposition, could provide a more granular view of cross-market volatility transmission (Diebold & Yilmaz, 2012).

4.9. Conclusion, Recommendations, and Future Research

This study investigated the statistical properties, macroeconomic influences, and strategic responses of LPE (LPE) investments in South Africa. The findings validate the following key hypotheses shown in Table 4-16:

Table 4-16. Hypotheses Validation Summary

Hypothesis	Validation Status	Key Findings
H1	Validated	Significant non-normality in returns.
H2	Validated	Strong evidence of volatility clustering.
H3	Validated	Inflation (-) and GDP (+) impact returns.
H4	Partially Validated	Moderate, short-lived spillovers.

Source: *Researchers Compilation*

The authors propose targeted recommendations for investors, policymakers, and corporate strategists to enhance the stability and performance of South Africa's LPE market. The study confirms that inflation exerts a strong negative influence on LPE returns, while GDP growth has a modest positive impact, aligning with existing research on macroeconomic volatility in emerging markets (Damodaran, 2018a; Gompers & Lerner, 1999). These findings emphasize the need for robust investment strategies, regulatory frameworks, and corporate adaptations to navigate market uncertainties effectively.

Investors should employ inflation-linked securities and commodities to mitigate inflation risks, a key driver of LPE returns (Damodaran, 2018b). Advanced models like GARCH and FIEGARCH enable better anticipation of market dynamics (Baillie et al., 1996; Bollerslev, 1986). Leveraging weak spillover effects in South Africa's LPE market offers diversification opportunities while monitoring global markets mitigates external risks (Engle, 2002); Karunanayake, 2011). Portfolio diversification across resilient sectors, inflation-hedging strategies, and volatility-based risk management can optimize returns amid inflation-driven uncertainty. GARCH-based forecasting models can further assist in identifying periods of heightened volatility, enabling timely investment adjustments (Bollerslev, 1986).

Policymakers should adopt inflation-targeting policies to stabilize the macroeconomic environment and enhance investor confidence (Teece et al., 1997). Supportive regulatory frameworks are needed to encourage advanced risk management tools, like derivatives for hedging (Hull, 2012). Addressing country-specific risks, such as political instability and regulatory uncertainty, is vital for fostering a stable private equity investment climate (Dopke et al., 2018). Implementing inflation-targeting measures, ensuring regulatory stability, and fostering macroeconomic resilience are critical to enhancing market confidence and promoting private equity growth. Strengthening capital markets and tax incentives for LPE firms can further attract investment.

Corporate strategies in South Africa effectively address volatility through diversification, hedging, and sectoral shifts, leveraging stable industries like healthcare and renewable energy to mitigate risks (Porter, 1985; Teece et al., 1997). Insights from long-memory models like FIEGARCH help firms align their strategies with persistent volatility patterns, optimizing resources and leveraging market fluctuations as a competitive advantage (Baillie et al., 1996; Barney, 1991). Sectoral shifts, derivative-based risk management, and adaptive planning are key to maintaining financial resilience. Firms that proactively integrate long-memory volatility models into strategic decision-making are positioned to mitigate risk and sustain competitive advantage (Teece et al., 1997).

Diversification plays a key role, as seen with Anglo-American investments in renewable energy projects, stabilizing revenue amidst commodity price fluctuations (Markowitz, 1952; Valadkhani & Chen, 2014). Similarly, Exxaro Resources' expansion into renewable energy reduces dependency on coal, demonstrating resilience in volatile sectors (Baker, 2015). Hedging strategies are equally critical, exemplified by Sasol's use of forward contracts and derivatives to mitigate oil price volatility, which was particularly effective during the 2020 COVID-19 disruptions (Hull, 2018; Sebehela, 2009). Standard Bank's currency hedging counters Rand volatility in banking, which is crucial for its operations across Africa (Nyakurukwa & Seetharam, 2024). Sectoral shifts also enhance stability, as shown by Mediclinic International and Aspen Pharmacare, which focus on healthcare to leverage consistent demand during economic downturns (Visser, 2019). Eskom's shift toward renewable energy aligns with global climate policies, mitigating risks tied to fossil fuel price volatility (Baker, 2017). These strategies align with theoretical frameworks. Dynamic Capabilities Theory emphasizes resource reconfiguration to adapt to volatility (Teece et al., 1997), while the Resource-Based View highlights leveraging internal capabilities for resilience (Barney, 1991). Contingency Theory supports tailoring strategies to external conditions, such as shifting energy demands (Burns & Stalker, 1961).

Empirical validation from GARCH-family models underscores these strategies' effectiveness. GARCH (1,1) highlights short-term volatility clustering, emphasizing the need for real-time risk management in volatile sectors like mining and banking (Bollerslev, 1986; Nelson, 1991). Anglo-American's integration of renewable energy demonstrates the strategic transformation of volatility into opportunity, while Mediclinic and Aspen Pharmacare showcase the stability of defensive industries like healthcare. In summary, South African firms proactively adapt their strategies to navigate and shape market volatility, leveraging theoretical insights and empirical evidence to enhance resilience and maintain a competitive edge in a challenging economic landscape.

Future research should explore cross-market spillovers in emerging economies (Engle, 2002), use alternative methods like Granger Causality and Variance Decomposition for deeper market insights (Dickey & Fuller, 1979), and conduct sector-specific studies in South Africa's LPE market to identify tailored strategies. Evaluating inflation-targeting policies and stabilization programs' long-term effects on private equity and analyzing investor behavior's role in volatility can further enhance understanding (Cont, 2001). By adopting these strategies and expanding research, stakeholders can better navigate South Africa's LPE market, ensuring resilience and sustainable growth.

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